

Constrained Non-linear Multi-objective Optimization of Preventive Maintenance Scheduling for Offshore Wind Farms

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Abstract

Offshore wind farm is an emerging source of renewable energy, which has been shown to have tremendous potential in recent years. In this blooming area, a key challenge is that the preventive maintenance of offshore turbines should be scheduled reasonably to satisfy the power supply without failure. In this direction, two significant goals should be considered simultaneously as a trade-off. One is to maximise the system reliability and the other is to minimise the maintenance related cost. Thus, a non-linear multi-objective programming model is proposed including two newly defined objectives with thirteen families of constraints suitable for the preventive maintenance of offshore wind farms. In order to solve our model effectively, the nondominated sorting genetic algorithm II, especially for the multi-objective optimisation is utilized and Pareto-optimal solutions of schedules can be obtained to offer adequate support to decision-makers. Finally, an example is given to illustrate the performances of the devised model and algorithm, and explore the relationships of the two targets with the help of a contrast model.

Keywords: Reliability, Maintenance, Scheduling, Cost Parameters, Offshore Wind Farms, Multi-objective Programming.

1. Introduction - Motivation

The wind energy capacity currently installed in the European Union (EU) can produce 284 TWh of electricity in an average wind year, which is enough to cover 10.2% of the EU's total

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electricity consumption.¹

At present, offshore wind power accounts for almost 1.1% of the EU's *total* capacity in the electricity consumption. Obviously, offshore wind farms are emerging to be one of the driving sources of energy in the green power world. In the US in May 2014, the U.S. Department of Energy awarded three multi-million demonstration projects planned for the New Jersey, Oregon and Virginia coasts. In theory, the potential benefit and challenge are tremendous [39]. In Germany, the ambitious *Energiewende* (energy transition) programme hopes to generate at least 35% of its electricity from the green renewable energy by 2020, and by 2050 the share is expected to surpass 80%. Again, offshore wind farms in north coastal parts of Germany play a key role in this direction [42]. Last, but not least, it should also be mentioned the Chinese government is giving considerable weight to exploiting this environmentally friendly resource of energy, particularly along the south-eastern part of its coast line [7].

Maintenance is classified into two main categories: the *corrective* and the *preventive* maintenance. The former one is usually performed after a system failure or breakdown while the latter one corresponds to the scheduled actions, which are performed while the system is still operational. Generally speaking, the *preventive maintenance* (PM) is more beneficial as it may prevent serious losses due to unpredicted failures [32].

This paper is aimed at the PM scheduling of offshore wind farms. For generalised power systems, the primary goal of the PM is to *avoid* or *mitigate* failure consequences of the electrical and mechanical parts of the system caused by fatigue cumulative damages and corrosion resistance degradations. PM is able to prevent faults effectively either before they occur or before they develop into major defects. *Scheduling* means to determine the most satisfied arrangement for the downtime of elements in offshore wind farms that need to be preventively maintained. Hence, our PM scheduling of offshore wind farms is transformed to an interesting optimisation problem, which is useful to different decision-makers in the green energy world.

The rest of the paper is organized as follows. In Section 2, a discussion about the new reliability and economic criteria is provided. Section 3 introduces and reviews the algorithm used for solving our problem. A non-linear multi-objective programming model with thirteen families of constraints for the PM scheduling of offshore wind farms is formulated, as well as its contrast model using the squares of net reserves minimisation objective in Section 4. Then, the technical parts of Nondominated Sorting Genetic Algorithm II (NSGA-II) are presented in

¹The UK remains in Europe with the largest amount of installed offshore wind capacity (45.9%), followed by Germany (29.9%), Denmark (11.5%), Belgium (6.5%), the Netherlands (3.9%) and Sweden (1.8%) (more details can be found in the EWEA's report [47]).

Section 5 and Appendix A. The effectiveness and performance of the proposed and contrast models are illustrated by presenting a numerical example in Section 6, and the results are analysed and compared from three main respects.

2. Objective Functions

Reliability and economic criteria are the two most popular objectives for the maintenance optimization models of power systems according to the literature to date. However, only a few studies have investigated the maintenance problem particularly designed for the offshore wind energy sector. In the following subsections, an analysis of the two criteria is provided.

2.1. Reliability Criterion

In terms of the reliability criterion, there are commonly two mainstream definitions. The first one is related to the required net power reserves to provide the stability in meeting the customer demand, and the second one indicates the deviation of the net power reserves, i.e., the reserve margin. The net power reserve is the balance of the gross reserve after deducting the maintenance loss. For the first type of the reliability measure, Kralj and Petrović [27] suggested that the net reserve generation can be maximised as an optimality criterion. Later, Conejo et al. [6] made a further development and first defined the reliability as the net reserve being divided by the gross reserve. This formulation soon became a classical objective for the maximisation of PM scheduling models. Canto [3] employed it to solve the PM scheduling problem of power plants, and then Canto and Romero [4] extended its application to the problems associated with wind farms integrated power plants.

For the second type of reliability perspective, Egan et al. [16] first proposed that the minimization of the sum of the *squares of the reserves* (SSR) would prevent the large variations in the net power reserves of each time period, which means the maximization of the reliability. There followed an upsurge in the use of this reliability definition by other scholars, [1, 8, 10, 11, 17, 43].

In our paper, we will *adjust* the first type of the conventional reliability criterion in the PM scheduling of offshore wind farms to model the behavioral attitude of our treatment. As only the customer power demand satisfaction delineated by the power reserve ratio has been studied in the previous definitions from the demand perspective, here the reliability criterion can be better depicted if the decision-maker preferences are also taken into account over a set of choices or attitudes. Moreover, in offshore wind farms, the particularly complex and variable marine environment contributes to the effects of the maintenance and degeneration on

the real power reserve which may not have such significant influence on other kinds of power plants [42]. Therefore, another factor, the *system sustainability*, which means the sustainable capability of reserving the power under the combined impacts of the maintenance work and the system degradation in each time period, is of equal importance to be considered in the reliability frame. It can reflect the actually attained power reserve ratio by exponentially adjusting the estimated power reserve ratio. Thus, we propose a novel non-linear definition of the reliability with both of the demand and supply side regards by introducing what we call the “*attainment exponent*”², so as to describe the decision-maker’s preferences, the power demand satisfaction and the system sustainability simultaneously.

2.2. Economic Criterion

With respect to the economic criterion (i.e., the maintenance related cost measure), the minimisation of the cost is always a unified objective definition for almost all maintenance scheduling problems with economic targets. Differences are mainly located in the diverse ingredients of the maintenance cost in different models. The amount of literature in this direction is vast, as many researches have introduced different economic criteria, [12, 23, 25, 31, 40], which have discussed in the offshore wind energy sector. In representative works summarized in Table 1, one can see that there are basically 8 kinds of costs related to the maintenance of power systems: *power production, maintenance, start-up, fixed, variable, opportunity, compensation, and failure costs*. Specifically, the *power production* and *maintenance* costs are the two fundamental costs mostly taken into account when building a cost minimisation objective, and the remaining types of costs are used in different degrees. According to Dahal et al. [9], Ding and Tian [14] and Zhang et al. [52], the market related maintenance costs³ and the accompanying *compensation* cost⁴ can usually be found in both the preventive and corrective maintenance, while the *failure* cost (i.e., cost of repair or replacement because of failures) arises only after the breakdown has happened in the mechanical system.

In order to cater to the PM without a power shortage or system failure in this paper, we refer to the definitions of the no-failure maintenance cost presented by Dahal et al. [9] and Dalgic et al. [12] to some degree, including the classical *maintenance* cost (direct and indirect costs), the *start-up* cost, the *fixed* cost, the *variable* cost and the *opportunity* cost, owing to opportunity foregone as the economic criterion of our PM scheduling problem of offshore wind

²This can also be seen a curvature parameter in the reliability index, see Section 4.2.1.

³The *opportunity* cost which partly means the revenue loss due to the power shortage caused by the maintenance outage.

⁴The cost to purchase electricity from other markets to meet customer requirements.

Table 1: Literature of the maintenance related cost composition for power systems

Literature	Power production cost	Maintenance cost	Start- up cost	Fixed cost	Variable cost	Opportunity cost	Compensation cost	Failure cost
Marwali & Shahidehpour [35]	✓	✓						
Leou [29]	✓	✓						
Chattopadhyay [5]	✓	✓		✓	✓		✓	
Conejo et al. [6]	✓	✓	✓	✓				
Canto [2]	✓	✓	✓					
Feng et al. [20]	✓	✓						✓
Ding & Tian [14]		✓			✓			✓
Ekpenyong et al. [17]	✓	✓	✓					
Zhang et al. [52]		✓	✓	✓		✓	✓	
Doostparast et al. [15]		✓					✓	✓
El-Sharkh [18]	✓	✓						
Fattahi et al. [19]	✓	✓		✓				
Mollahassani-pour et al. [37]	✓	✓						
Dahal et al. [9]		✓				✓	✓	✓
Dalgic et al. [12]	✓	✓	✓	✓	✓			
Gundegjerde et al. [23]		✓		✓	✓		✓	
Lagaros et al. [28]		✓		✓		✓		✓
Lv et al. [34]		✓					✓	✓

farms. Although the power production cost is used in most of the literature, it is not imported in our model because we attribute it to its weak relationship with maintenance works. In addition, some other cost factors particularly for wind farms are also involved in our definition as indicated by Ding and Tian [14] and Gundegjerde et al. [23], e.g., the *fixed* cost of sending vessels to wind farms for maintenance, the *variable* access cost to wind turbines, etc. Thus, a new rational and *offshore wind farm-oriented maintenance related cost* criterion is well built to conduct an overall weighting.

3. Optimization Technique

There are different approaches of multi-objective optimisation for mechanical systems [22, 33]. Since reliability and economic criteria are both very important for maintenance scheduling problems of power systems, they should be treated equally to implement a simultaneous optimisation. Actually, models commonly set either reliability maximisation or maintenance cost minimization as their objective functions. Lack of studies on the multi-objective optimisation with classical reliability and cost criteria is a challenge to decision-makers. It is difficult for them to get effective solutions for a reasonable assignment of the two elements in the maintenance scheduling. Therefore, in this paper, for the first time, according to the authors' knowledge, a constrained non-linear multi-objective programming model is constructed for the PM scheduling of offshore wind farms in order to maximise the reliability and minimise the maintenance cost concurrently. Furthermore, for better understanding the performance of the proposed model, we also raise a contrast model, in which the only difference is that the reliability objective is replaced by the SSR minimisation definition. [Thus, the relationship between reliability and maintenance cost objectives can be deeply studied by analyzing the trade-offs between the two goals, as well as comparing them using the proposed as well the contrast model.](#)

With respect to the solving methods of the designed multi-objective programming model, the most classical way is to transform it into a single-objective model by the weighted sum approach. As the reliability and maintenance cost objectives with different measures are conflicting with each other, only the sacrificing on one objective can make the other closer to the optimal goal. Thus, this obviously makes the weight setting a process with strong subjectivity and the availability of optimisation results becomes badly affected. Moreover, when such a method is used for seeking multiple satisfying solutions, it has to be applied many times, hopefully finding a different solution at each iteration. If more solutions cannot be obtained, decision-makers are unable to evaluate each objective by the single solution effectively. In order to overcome the shortcomings, *multi-objective evolutionary algorithms* (MOEAs) are proposed for

their ability to find multiple Pareto-optimal solutions in a single simulation run. The first MOEA, called *vector evaluated genetic algorithm* (VEGA) was proposed by Schaffer [41]. An algorithm called *nondominated sorting genetic algorithm* (NSGA) based on the nondominated sorting is proposed by Srinivas and Deb [45]. It was later developed by Deb et al. [13] and named *NSGA-II*, which alleviates high computational complexity of the nondominated sorting, lack of the elitism and use of the sharing parameter.

MOEAs are employed to solve some multi-objective maintenance scheduling models for power systems. Leou [30] put forward a *genetic algorithm* (GA) combined with the *simulated annealing* method to solve the unit maintenance scheduling problem with the fitness maximisation objective composed by reliability and cost indices. In the maintenance scheduling optimisation in Yang et al. [50], the Markov model was used to handle reliability and cost objectives, and then in Yang and Chang [49], the same model was rebuilt for energy not served, and operation and expected failure cost objectives. Both models were solved by NSGA-II, so with the imperfect PM maintenance model in Wang and Pham [48]. Zhan et al. [51] designed a multi-objective generation maintenance scheduling model, in which five objectives containing the profit maximisation, SSR minimisation and generation cost minimisation were optimized by *group search optimizer with multiple producers*.

Hence, in our paper, we utilize the NSGA-II, which is able to find a much better spread of solutions and better convergence near the true Pareto-optimal front when compared to other MOEAs, to solve our constrained non-linear multi-objective programming model for the PM scheduling of offshore wind farms. After decision-makers obtain Pareto-optimal solutions from the algorithm, they need to analyse the results and make trade-off decisions for determining an appropriate satisficing solution to support the offshore wind farm project.

4. Mathematical Model Formulation

In this section, the formulation of the multi-objective programming model is presented with the objectives of reliability maximization and cost minimisation under several realistic constraints for the PM scheduling problem of offshore wind farms.

4.1. Notations

Before we proceed further, indices, parameters and decision variables used in this paper are introduced in Table 2.

Table 2: Notations for the PM scheduling problem of offshore wind farms

m	number of turbines in wind farm	H_i	helicopter need for maintaining TR_i
i	index of offshore wind turbines	LP_i	maintenance duration TR_i requires
n	number of periods in time horizon	C^{FV}	per unit fixed cost (€) of vessels
t	index of time periods	C^{FH}	per unit fixed cost (€) of helicopters
TR_i	the i th turbine	$C_{i,t}^T$	total transport cost (€) of TR_i in PR_t
PR_t	the t th time period	$C_{i,t}^A$	adjustment cost (€) for TR_i in PR_t
$p_{i,t}$	power (MW) generated by TR_i in PR_t	$C_{i,t}^{CRM}$	customer relationship management cost (€) for TR_i in PR_t
d_t	power (MW) required in PR_t	$C_{i,t}$	total maintenance cost (€) for TR_i in PR_t
s_t	attainment exponent affecting power demand satisfaction in PR_t , $s_t \geq 0$	U	time period set not allowed for maintenance
E_t	gross power reserve (MW) in PR_t	LT_t	turbine maintenance capacity in PR_t
e_t	net power reserve (MW) in PR_t	L_i	maintenance deadline of TR_i (PR_{L_i})
r_t	reliability (%) in PR_t	AM_t	number of available manpower in PR_t
R	system reliability (%) of wind farm	AV_t	number of available vessels in PR_t
C_t^{MV}	vessel manpower cost (€) in PR_t	AH_t	number of available helicopters in PR_t
C_t^{MH}	helicopter manpower cost (€) in PR_t	z_i	distance (km) from shore to TR_i
C_t^{ML}	onshore manpower cost (€) in PR_t	q^V	vessel gas emission (kg/kg·km)
M_i^V	vessel manpower demand for TR_i	q^H	helicopter gas emission (kg/kg·km)
M_i^H	helicopter manpower demand for TR_i	\bar{w}	average weight of an employee (kg)
M_i^L	onshore manpower demand for TR_i	EQ_i^V	equipment (kg) on vessels for TR_i
$C_{i,t}^M$	total manpower cost (€) for TR_i in PR_t	EQ_i^H	equipment (kg) on helicopters for TR_i
$C_{i,t}^{EQ}$	equipment cost (€) for TR_i in PR_t	LV_t	permitted moving vessels in PR_t
$C_{i,t}^I$	infrastructure cost (€) for TR_i in PR_t	LH_t	permitted moving helicopters in PR_t
$C_{i,t}^{EM}$	environmental monitoring cost (€) for TR_i in PR_t	GHG	greenhouse gas emission standard regulated by the industry (kg)
$C_{i,t}^{SV}$	unit vessel transport cost (€) for TR_i in PR_t	$x_{i,t}$	0-1 decision variable denoting the maintenance status of TR_i in PR_t
$C_{i,t}^{SH}$	unit helicopter transport cost (€) for TR_i in PR_t	$b_{i,t}$	0-1 decision variable denoting the starting state of TR_i in PR_t
V_i	vessel demand for maintaining TR_i		

4.2. Mathematical Formulation of Objective Functions

Our aim is to allocate m turbines in offshore wind farms to implement their maintenance in different time periods, taking into account optimising the system reliability and the maintenance cost simultaneously. Since the two goals are contradicting, satisfying results can be derived only after recommending appropriate trade-off decision-making strategies.

4.2.1. System Reliability Maximization Objective

The first objective function is to maximise the system reliability. The reliability of the whole offshore wind farm system means the customer demand satisfaction for enough electricity is reserved, and simultaneously to consider the effects of the sustainability.

In our problem, dual influences to the system reliability which are brought by maintenance are taken into consideration. On the one hand, there should always be sufficient power generated for normal market consumption and inevitably for satisfying on-peak demand while some turbines stop working due to maintenance. Therefore, performing the necessary maintenance makes the energy generation decrease, resulting in increasing the probability that the power demand cannot be fully satisfied. On the other hand, the maintenance can fight against corrosion and the degradation of the substructures of turbines, and attempts to [reduce the risk of serious grid breakdowns](#). Thereby, three different possible effects emerge to provide actual achievements of the customer power demand satisfaction, i.e., the power reserve ratio. One is that the service life of turbines is extended and the sustainable development of the system is promoted, another is that the system maintains balance to guarantee the average level, and the third is that the system is still getting worse after maintenance because of some deep-rooted or irreversible degenerations.

The system reliability R is the [average](#) of reliabilities r_t in all periods, which are defined as exponentials of the attainment factor s_t ⁵ with the base measuring the proportion of the net power reserve e_t to the gross power reserve E_t . Thus, the reliability r_t in PR _{t} is

$$r_t = (e_t/E_t)^{s_t}, \quad (1)$$

in which the gross power reserve E_t (MW) means to deduct the customer electricity demand from the amount generated by all turbines, i.e.,

⁵Actually, in this paper, we recommend for the very first time according to the authors' knowledge, the use of an isoelastic function (or in another word, the use of a power function) to model the behavioral attitude of our treatment, see Section 2.1. The isoelastic utility function is a special case of the hyperbolic absolute risk aversion (HARA) utility functions, and is used in analyses either including or not including the underlying risk. For more details, see [44] among numerous others.

$$E_t = \sum_{i=1}^m p_{i,t} - d_t, \quad (2)$$

and the net power reserve e_t (MW) also needs to subtract the shutdown loss of the energy production caused by the maintenance as

$$e_t = \sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t, \text{ where } x_{i,t} \in \{0, 1\}. \quad (3)$$

So the equivalent form of the reliability r_t in Eq. (1) is

$$r_t = \left[\frac{\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t}{\sum_{i=1}^m p_{i,t} - d_t} \right]^{s_t}. \quad (4)$$

It can be seen that the value of the power reserve ratio e_t/E_t partly reflects whether the system is reliable in PR_t . It is also noted the lower bound is that the power reserve should at least be enough to satisfy the customer requirement though some turbines stop working for maintenance, i.e., $e_t = 0$, $e_t/E_t = 0$, $r_t = 0$, and the upper bound is that the net power reserve equals to the gross power reserve when there is no turbine in maintenance in PR_t , i.e., $e_t = 1$, $e_t/E_t = 1$, $r_t = 1$.

Regarding the exponent, i.e., the attainment factor s_t , since the base is $e_t/E_t \in [0, 1]$, the reliability r_t decreases from 1 approaching to 0 with $s_t \in [0, +\infty)$ increasing according to properties of the exponential function. It also gives the power reserve ratio e_t/E_t three different kinds of effects by different parameter values as follows:

- (1) “*Positive*” effect: $r_t = (e_t/E_t)^{s_t} > e_t/E_t$, when $s_t \in [0, 1)$. The reliability index is upgraded by the decision-maker.
- (2) “*Neutral*” effect: $r_t = (e_t/E_t)^{s_t} = e_t/E_t$, when $s_t = 1$: This means that impact of the decision-maker is the same. There is neither an upgrade nor a downgrade of the reliability index.
- (3) “*Negative*” effect: $r_t = (e_t/E_t)^{s_t} < e_t/E_t$, when $s_t \in (1, +\infty)$: In this case, there is a downgrade.

Especially, for purpose of better understanding the *positive*, *neutral* and *negative* effects brought by different attainment exponents s_t , Fig. 1 provides an illustrative example of $r_t = (2/5)^{s_t}$, in which each point stands for a type of effect, respectively.

Since the electricity generated and demanded in each time period is an approximate estimate in terms of the historical data, the power reserve ratio e_t/E_t which has eliminated the influence of the maintenance downtime, as well as the attainment exponent s_t reflecting the effects of decision-makers attitude, can coordinate to represent the actual achievement of the customer power demand satisfaction. The power reserve ratio and the attainment exponent are two

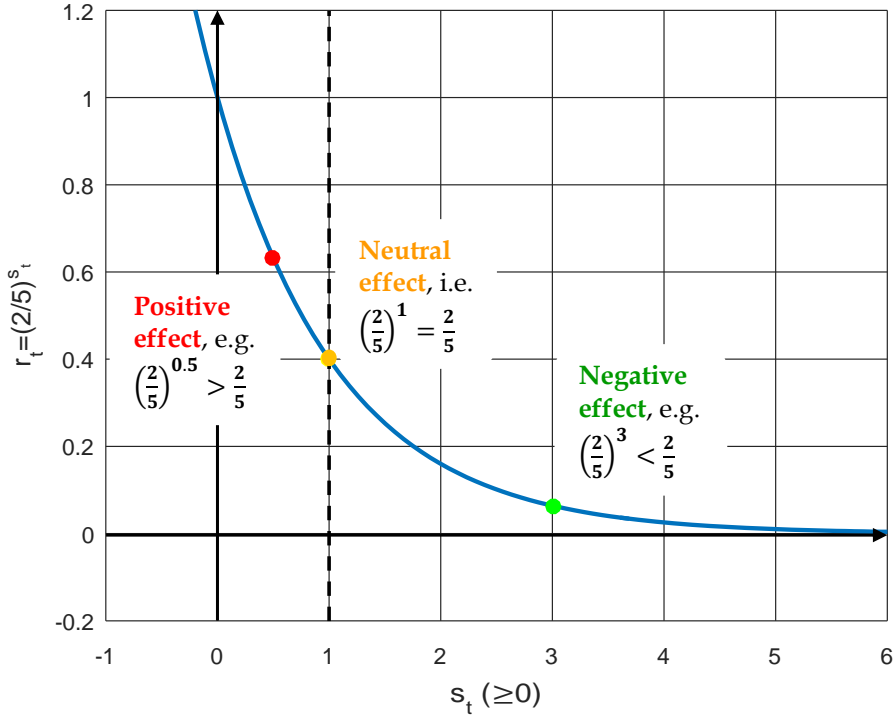


Fig. 1: An example for three types of effects of attainment exponents with $r_t = (2/5)^{s_t}$ and $s_t = 0.5, 1$ and 3 , respectively.

constitutive elements of the reliability r_t in PR_t . Then the system reliability R can be defined by averaging individual reliabilities r_t as

$$R = \sum_{t=1}^n \frac{1}{n} r_t, \quad (5)$$

in which the weight coefficient $1/n$ of r_t are for normalization to adjust R into the range $[0, 1]$.

According to Eqs. (1) and (4), the system reliability R is equivalent to

$$R = \sum_{t=1}^n \frac{1}{n} \left(\frac{e_t}{E_t} \right)^{s_t} = \sum_{t=1}^n \frac{1}{n} \left[\frac{\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t}{\sum_{i=1}^m p_{i,t} - d_t} \right]^{s_t}. \quad (6)$$

Notably, due to n reliabilities r_t constituting the final reliability R , it means that there are n attainment exponents s_t needed to be settled based on three different types of effects. As it is difficult to collect the exact data of the effects due to the unknown degradation status and the maintenance capability especially for newly grid-connected offshore wind farms, a feasible scheme is to draw support from the decision-maker's experience. Over the entire time horizon, decision-maker's attitudes and preferences to the maintenance versus degradation trend of the offshore wind power project. Thus, in what follows, we test some predefined behavioral attitudes of the decision-makers. Obviously, the proposed four categories, "fully rational", "optimism biased", "wait-and-see attitudes" and "pessimism biased" are initiating and inspiring, rather than exhaustive and conclusive for the research on maintenance, and more generally s-

peaking, in the behavioral approach of the reliability index and our multi-objective constrained optimization problem. So, let us define the four categories of attitudes:

(1) When decision-makers are *fully rational*, and all the three effects appear in sequence over the time. Specifically, they believe that if turbines are maintained as much as possible in the early stage of all n periods, attainment exponents s_t give the customer demand satisfaction positive impacts because it is not only easier to solve the degradation but also benefits the system survivability for the duration. When it comes to the mid-term stage, the effects of s_t tend to be neutral as the system performance gradually weakens. Along with the continuous decline, no matter that the turbines have already been maintained before the latter stage or are precisely in maintenance, the advantages from the maintenance are overtaken by cumulative damages and failure risks. Accordingly, negative influences of s_t on customer satisfaction occur in the latter stage. Therefore, attainment exponents s_1, s_2, \dots, s_n are selected from the three sets $[0, 1), \{1\}, (1, +\infty)$.

(2) When decision-makers are *optimism biased*, they are always inclined to think that a higher real customer demand satisfaction on positive effects of attainment exponents s_t can be reached. It means that the maintenance is able to overwhelm the deterioration over all n periods and the system reliability remains at a high level. Therefore, when decision-makers have such a preference, all attainment exponents s_1, s_2, \dots, s_n are chosen from the interval $[0, 1)$.

(3) When decision-makers take *wait-and-see attitudes*, which refer to no clear or specific preference firmly in mind, they think that efforts of the maintenance and the deterioration can be perceived as merits equal demerits. No bias on the real achieved customer satisfaction and reliability happens in any period over the time horizon. Thus, all attainment exponents s_1, s_2, \dots, s_n equal to 1, i.e., no exponents when decision-makers are conservative, which suggests that it transforms to the first conventional reliability criterion of the PM scheduling (the power reserve ratio). Therefore, the classical power reserve ratio is included as one of the particular scenarios in our reliability formulation, so that the limitation of the original reliability design is reflected and improved.

(4) When decision-makers are *pessimism biased*, it is thought that negative effects of attainment exponents s_t take up whole time periods owing to all kinds of degradations and risks in the severe marine environment, even the maintenance is essentially not powerful enough to improve the instability of the wind farm system. Consequently, all attainment exponents s_1, s_2, \dots, s_n can be picked from the interval $(1, +\infty)$.

In accordance with the four kinds of decision-maker's attitudes, the system reliability R can be determined explicitly by the weighted sum of reliabilities r_t . Hence, the first non-linear

objective function of our model is the system reliability maximisation:

$$\max R = \max_{\mathbf{x}} \sum_{t=1}^n \frac{1}{n} \left[\frac{\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t}{\sum_{i=1}^m p_{i,t} - d_t} \right]^{s_t}. \quad (7)$$

4.2.2. Maintenance Cost Minimization Objective

The second objective function is to minimize the maintenance related cost. In the following, the seven costs including the *manpower*, *equipment*, *infrastructure*, *environmental monitoring*, *transportation*, *adjustment* and *customer relationship management* costs are introduced explicitly:

(1) *Manpower* cost $C_{i,t}^M$: the *direct maintenance* cost for technical and administrative labour in maintaining offshore wind farms, and the *indirect maintenance* cost for staff welfare. It can be expressed as

$$C_{i,t}^M = C_t^{MV} M_i^V + C_t^{MH} M_i^H + C_t^{ML} M_i^L, \quad (8)$$

where C_t^{MV} , C_t^{MH} , and C_t^{ML} are per capita manpower costs in PR_t for employees working on vessels, helicopters and land, and M_i^V , M_i^H , and M_i^L are corresponding amounts of manpower needed for maintaining TR_i .

(2) *Equipment* cost $C_{i,t}^{EQ}$: the *direct maintenance* cost for purchasing spare parts, material and equipment required for the maintenance of TR_i in PR_t , as well as the *indirect maintenance* cost for equipment storage and testing.

(3) *Infrastructure* cost $C_{i,t}^I$: the *start-up* cost of enabling infrastructures (i.e., ports, docks, helipads, etc.) that support the maintenance of TR_i in PR_t , and the *indirect maintenance* cost of operating and maintaining them.

(4) *Environmental monitoring* cost $C_{i,t}^{EM}$: the *indirect maintenance* cost of monitoring whether the maintenance activities seriously influence the marine environment around offshore wind farms beyond acceptable thresholds, i.e., the air and livings of marine creatures and bird species. Meanwhile, considering the complexity of the marine environment, dynamic monitoring is also essential for real-time weather forecasts on the sea, in order to judge whether it is appropriate for implementing the offshore maintenance of TR_i in PR_t .

(5) *Transportation* cost $C_{i,t}^T$: the *fixed* cost of employing and maintaining vessels and helicopters, and the *variable* cost of marine and air shipments to offshore wind turbines, including fuel cost and the cost of remaining at turbines for supporting maintenance activities. As to the maintenance of offshore wind farms, costs related to the manpower and equipment transportation account for a large proportion of the total maintenance related cost because of the special environment of the sea. It is formulated as

$$C_{i,t}^T = (C^{FV} V_i + C^{FH} H_i) / LP_i + (C_{i,t}^{SV} V_i + C_{i,t}^{SH} H_i). \quad (9)$$

The first term means the fixed cost for the use of vehicles, in which C^{FV} and C^{FH} are per unit fixed costs of vessels and helicopters when putting them into use, and V_i and H_i are the respective quantities of two vehicles the maintenance of TR_i requires. Since this cost is incurred once when starting using a vessel or helicopter, it is divided by LP_i , which is the maintenance duration time of TR_i . In the second term, $C_{i,t}^{SV}$ and $C_{i,t}^{SH}$ are average variable shipment costs per vessel and helicopter, along with their fuel costs and waiting costs for maintaining TR_i in PR_t .

(6) *Adjustment cost* $C_{i,t}^A$: the *opportunity* cost for adjusting the maintenance when the schedule needs to be altered because of changes in weather and power demand and some other emergency situations. As the maintenance is scheduled according to estimated data, some adjustments are required for the deployment of the maintenance. Thus the adjustment cost for TR_i in PR_t arises.

(7) *Customer relationship management (CRM) cost* $C_{i,t}^{CRM}$: the *opportunity* cost for maintaining the customer relationship. Although the maintenance aims at enhancing the system reliability of offshore wind farms, the risk of power shortage may increase due to the maintenance downtime. In order to retain customer satisfaction and loyalty, the CRM cost for TR_i in PR_t is invested to analyse customers, promote the benefits of the renewable wind energy, and make more long-term potential contracts possible.

Thus, the above seven elements constitute the total maintenance cost $C_{i,t}$ of TR_i in PR_t as

$$C_{i,t} = C_{i,t}^M + C_{i,t}^{EQ} + C_{i,t}^I + C_{i,t}^{EM} + C_{i,t}^T + C_{i,t}^A + C_{i,t}^{CRM}, \quad (10)$$

where each item stands for one ingredient of the PM cost for offshore wind farms. Thereby, the maintenance cost minimization objective function of our problem can be presented as

$$\min_{\mathbf{X}} \sum_{i=1}^m \sum_{t=1}^n C_{i,t} x_{i,t} = \min_{\mathbf{X}} \sum_{i=1}^m \sum_{t=1}^n (C_{i,t}^M + C_{i,t}^{EQ} + C_{i,t}^I + C_{i,t}^{EM} + C_{i,t}^T + C_{i,t}^A + C_{i,t}^{CRM}) x_{i,t}, \quad (11)$$

in which the manpower cost $C_{i,t}^M$ and the transportation cost $C_{i,t}^T$ are detailed by their definitions, respectively, see Eqs. (8) and (9).

Notably, the environmental monitoring cost $C_{i,t}^{EM}$ and the transportation cost $C_{i,t}^T$ are designed especially for the PM of offshore wind farms due to the specificity of the marine environment, while the other five costs can also apply to that of general power systems.

4.3. Constraints

The constraints should not only be well applicable for the PM scheduling problem of general power plants, but also carefully devised for that of offshore wind farms. In total, thirteen families of constraints are proposed: *supply and demand*, *maintenance necessity*, *maintenance continuity*, *duration*, *period*, *priority*, and *deadline* constraints are the basic ones for the PM scheduling problem of power systems, see [1, 4]. However, *weather*, *manpower*, *vehicle*, *greenhouse gas emission*, *marine ecosystem*, and *bird population* constraints are proposed by Dalgic et al. [12], Gundegjerde et al. [23], Hassan [24], Karyotakis [26] and Michler-Cieluch et al. [36], and particularly designed for offshore wind power systems coping with the harsh offshore environment.

4.3.1. Supply and demand constraints

The electric power virtually generated which has taken out the maintenance downtime loss should be able to cover the customer demand entirely. So the supply and demand constraints guarantee that the power shortage never occurs in any time period,

$$\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t \geq 0, \quad t = 1, 2, \dots, n, \quad (12)$$

which are namely to restrict net power reserves e_t (MW) in Eq. (3) no less than 0.

4.3.2. Maintenance necessity constraints

The maintenance of wind turbines that are especially located offshore costs enormous manpower and material resources, so every turbine is set to be maintained only once over the time horizon without any pause halfway,

$$\sum_{t=1}^n b_{i,t} = 1, \quad i = 1, 2, \dots, m. \quad (13)$$

This means for any TR_i , it needs to be maintained once and for all during all n time periods.

4.3.3. Maintenance continuity constraints

When TR_i starts to be maintained, it enters the downtime and maintenance works cannot be stopped before they are all finished. The maintenance continuity constraints clarify the relationships between the two sets of decision variables $x_{i,t}$ and $b_{i,t}$. The decision variables meet the following logical relationships

$$x_{i,t} \geq b_{i,t}, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n, \quad (14)$$

which imply that when $b_{i,t} = 1$, $x_{i,t} = 1$ must hold. It means that when TR_i begins maintenance at the beginning of PR_t , it must be in maintenance during the whole period. Moreover, Eq. (14) shows that when $b_{i,t} = 0$, $x_{i,t} = 0$ or 1, i.e., if the maintenance of TR_i does not start at PR_t , it may not or may still be in maintenance in this period. Besides, another two additional relationships are derived as follows,

$$\begin{aligned} x_{i,t} - x_{i,t-1} &\leq b_{i,t}, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n, \\ x_{i,t} + x_{i,t-1} + b_{i,t} &< 3, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n, \end{aligned} \quad (15)$$

where $x_{i,t-1} = 0$ when $t = 1$. They limit the relationships of maintenance activities in two successive time periods PR_{t-1} and PR_t .

4.3.4. Duration constraints

As to TR_i , the duration of periods for its maintenance is predetermined and fixed by the project. The maintenance duration constraints limit are

$$\sum_{t=1}^n x_{i,t} = LP_i, \quad i = 1, 2, \dots, m, \quad (16)$$

where LP_i is the number of time periods that TR_i needs for maintenance.

4.3.5. Period constraints

In any PR_t , the power generation needs to satisfy the demand market. As turbines in maintenance stop working and have no electricity to output, the total number of turbines in maintenance in PR_t should be restricted to an upper limit.

$$\sum_{i=1}^m x_{i,t} \leq LT_t, \quad t = 1, 2, \dots, n, \quad (17)$$

where LT_t is the presupposed limit of turbines shut down in PR_t .

4.3.6. Priority constraints

Sometimes the maintenance of a single turbine needs to be fully done before another due to a variety of reasons, so the priority constraints set the precedence of the maintenance for two different turbines over the time horizon. We assume that the maintenance of TR_i is prior to that of TR_j , then

$$\sum_{k=1}^t b_{i,k} - b_{j,t} \geq 0, \quad i = 1, 2, \dots, m, \quad j \neq i, \quad t = 1, 2, \dots, n, \quad (18)$$

where k represents the index of time periods from TR_1 to TR_t , and

$$x_{i,t} + x_{j,t} \leq 1, \quad i = 1, 2, \dots, m, \quad j \neq i, \quad t = 1, 2, \dots, n. \quad (19)$$

It can be seen that the whole maintenance duration of TR_i should remain ahead of that of TR_j , and there is not any overlap period between the maintenance of the two turbines.

4.3.7. Deadline constraints

In some cases, the maintenance of a turbine has a deadline. If the maintenance of TR_i is stated to be accomplished by the end of PR_{L_i} , there is a deadline constraint to compel TR_i to start maintaining no later than $PR_{L_i-LP_i+1}$ as,

$$\sum_{t=1}^{L_i-LP_i+1} b_{i,t} = 1, \quad i = 1, 2, \dots, m. \quad (20)$$

Thus, TR_i would have enough time to finish the maintenance before its deadline.

4.3.8. Weather constraints

The weather constraints are particular to the natural marine environment that only offshore wind energy confronts. Considering the complex and volatile weather conditions such as wind speed, wave height, flight visibility, marine storm, etc., the maintenance of offshore wind farms cannot be implemented in some periods [39]. For instance, the wind in winter is usually stronger than in other seasons, so the use of vessels, helicopters and crews are unsafe for use for maintenance in winter. Additionally, the high wind speed results in the rise of energy production and the customer electricity demand also increases considerably during the winter season. These weather factors encourage decision-makers to arrange maintenance in winter as little as possible. The weather constraints which restrict the maintenance execution are formulated as follows,

$$\sum_{t \in U} x_{i,t} = 0, \quad i = 1, 2, \dots, m, \quad (21)$$

where U is the set of periods not permitted for maintenance due to the weather effect on the sea.

4.3.9. Manpower constraints

In any period t , crew numbers related to the maintenance should be guaranteed. Manpower, both for maintenance activities to offshore wind turbines by vessels and helicopters and for remote monitoring, control and logistics onshore cannot exceed the total available number of employees in PR_t . Thus, the manpower constraints are expressed as

$$\sum_{i=1}^m (M_i^V + M_i^H + M_i^L) x_{i,t} \leq AM_t, \quad t = 1, 2, \dots, n, \quad (22)$$

where M_i^V , M_i^H , and M_i^L , respectively stand for all technical and administrative manpower required on vessels and helicopters and on land for maintaining TR_i , and AM_t is the total

number of idle employees in PR_t .

4.3.10. Vehicle constraints

Vessels and helicopters are vehicles for transiting crews and equipment from shore side to offshore turbines to operate maintenance works. The vehicle constraints restrict the numbers of vessels and helicopters used for maintenance in PR_t , which cannot exceed the total available number of vehicles in that period. Similar to the forms of the above manpower constraints, the vehicle constraints can be presented separately for vessels and helicopters as

$$\begin{aligned} \sum_{i=1}^m V_i x_{i,t} &\leq AV_t, \quad t = 1, 2, \dots, n, \\ \sum_{i=1}^m H_i x_{i,t} &\leq AH_t, \quad t = 1, 2, \dots, n, \end{aligned} \quad (23)$$

where V_i and H_i are numbers of vessels and helicopters TR_i requires, respectively to transport manpower and equipment for offshore maintenance according to different turbine locations, and AV_t and AH_t are the corresponding unoccupied vehicle numbers in PR_t .

4.3.11. Greenhouse gas emission constraints

Vessels and helicopters used to transfer crews and equipment for offshore maintenance are supplied with fossil fuel, and then discharge various greenhouse gases mainly including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF_6). These gases pollute the atmosphere, and cause greenhouse effect and global warming as well. Therefore, greenhouse gas emissions (g/km) in the maintenance system should also strictly comply with national emission standards. Thus, to be an environmentally friendly offshore wind energy project, the total gas emission mass of transfer vessels and helicopters in any period over the maintenance time horizon can be no more than the industrial emission standard as follow,

$$\sum_{i=1}^m 2z_i b_{i,t} [q^V (\bar{w} M_i^V + EQ_i^V) + q^H (\bar{w} M_i^H + EQ_i^H)] \leq GHG, \quad t = 1, 2, \dots, n, \quad (24)$$

where z_i is the distance (km) from the docking point onshore to TR_i offshore, q^V and q^H (kg/kg·km) are respective kilograms of greenhouse gases that vessels and helicopters emit per kilogram weight of the items they bear for transport per kilometre, M_i^V and M_i^H , respectively represent the number of manpower required on vessels and helicopters for maintaining TR_i , \bar{w} means the average weight (kg) of an employee, EQ_i^V and EQ_i^H indicate the weight (kg) of the equipment carried by vessels and helicopters, respectively for the maintenance of TR_i , and GHG is the emission standard (kg) regulated by the industry.

4.3.12. Marine ecosystem constraints

Apart from the atmospheric pollution transport vehicles for maintenance of offshore wind farms bring about, they also make contributions to the ecosystem. Fleets of vessels, the primary vehicles navigating on the sea for maintenance activities disturb the living environment of marine species to some extent. For example, the fuel leakage and marine litter from vessels shuttling back and forth can damage the living environment of marine life. The movement and noise they make scare the fish school, and can have negative effects on fish migration and also influence the mariculture. In order to protect the marine ecosystem from impacts of moving vessels, the number of navigating vessels in PR_t should be no more than the ceiling stipulated by the project based on actual marine situations as

$$\sum_{i=1}^m V_i(b_{i,t} + b_{i,t-LP_i+1}) \leq LV_t, \quad t = 1, 2, \dots, n, \quad (25)$$

where V_i is the amount of vessels to transit for TR_i , $b_{i,t}$ and $b_{i,t-LP_i+1}$ are respective indications of vehicles out and return journeys because of offshore maintenance in PR_t , and LV_t is the total permitted amount of moving vessels in each period.

4.3.13. Bird population constraints

Low-flying helicopters on out and return journeys for offshore maintenance impact the life and migration of the bird population. Since birds are sensitive to human disturbance, special care is required when using helicopters to transit crews and equipment for maintenance, in order to avoid causing difficulties for birds or endangering their lives. Hence, the number of navigating helicopters in each period should be tightly controlled for bird population protection. It cannot exceed the upper limit LH_t in PR_t as

$$\sum_{i=1}^m H_i(b_{i,t} + b_{i,t-LP_i+1}) \leq LH_t, \quad t = 1, 2, \dots, n, \quad (26)$$

where H_i is the helicopter quantity for transportation while maintaining TR_i , and the bird population constraints have similar formulations to the marine ecosystem constraints proposed above.

4.4. Multi-objective Programming Model and Contrast Model

In terms of the above two objective functions and thirteen constraints, a non-linear multi-objective programming model for our maintenance scheduling optimisation problem of offshore wind farms is proposed as follows,

$$\left\{ \begin{array}{l} \max_{\mathbf{X}} \sum_{t=1}^n \frac{1}{n} \left[\frac{\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t}{\sum_{i=1}^m p_{i,t} - d_t} \right]^{st} \\ \min_{\mathbf{X}} \sum_{i=1}^m \sum_{t=1}^n (C_{i,t}^M + C_{i,t}^{EQ} + C_{i,t}^I + C_{i,t}^{EM} + C_{i,t}^T + C_{i,t}^A + C_{i,t}^{CRM}) x_{i,t} \end{array} \right. \quad (27a)$$

subject to:

$$\begin{aligned} \sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t &\geq 0, \quad t = 1, 2, \dots, n \\ \sum_{t=1}^n b_{i,t} &= 1, \quad i = 1, 2, \dots, m \\ x_{i,t} &\geq b_{i,t}, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n \\ x_{i,t} - x_{i,t-1} &\leq b_{i,t}, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n \\ x_{i,t} + x_{i,t-1} + b_{i,t} &< 3, \quad i = 1, 2, \dots, m, \quad t = 1, 2, \dots, n \\ \sum_{t=1}^n x_{i,t} &= LP_i, \quad i = 1, 2, \dots, m \\ \sum_{i=1}^m x_{i,t} &\leq LT_t, \quad t = 1, 2, \dots, n \\ \sum_{k=1}^t b_{i,k} - b_{j,t} &\geq 0, \quad i = 1, 2, \dots, m, \quad j \neq i, \quad t = 1, 2, \dots, n \\ x_{i,t} + x_{j,t} &\leq 1, \quad i = 1, 2, \dots, m, \quad j \neq i, \quad t = 1, 2, \dots, n \\ \sum_{t=1}^{L_i - LP_i + 1} b_{i,t} &= 1, \quad i = 1, 2, \dots, m \\ \sum_{t \in U} x_{i,t} &= 0, \quad i = 1, 2, \dots, m \\ \sum_{i=1}^m (M_i^V + M_i^H + M_i^L) x_{i,t} &\leq AM_t, \quad t = 1, 2, \dots, n \\ \sum_{i=1}^m V_i x_{i,t} &\leq AV_t, \quad t = 1, 2, \dots, n \\ \sum_{i=1}^m H_i x_{i,t} &\leq AH_t, \quad t = 1, 2, \dots, n \\ \sum_{i=1}^m 2z_i b_{i,t} [q^V(\bar{w}M_i^V + EQ_i^V) + q^H(\bar{w}M_i^H + EQ_i^H)] &\leq GHG, \quad t = 1, 2, \dots, n \\ \sum_{i=1}^m V_i (b_{i,t} + b_{i,t-LP_i+1}) &\leq LV_t, \quad t = 1, 2, \dots, n \\ \sum_{i=1}^m H_i (b_{i,t} + b_{i,t-LP_i+1}) &\leq LH_t, \quad t = 1, 2, \dots, n \\ x_{i,t} &= 1 \text{ if TR}_i \text{ is in maintenance in PR}_t, = 0 \text{ otherwise,} \\ b_{i,t} &= 1 \text{ if the maintenance of TR}_i \text{ begins at PR}_t, = 0 \text{ otherwise,} \end{aligned} \quad (27b)$$

in which $x_{i,t}$ and $b_{i,t}$ are both decision variables. The model's target is to obtain a set of turbine maintenance schedules on condition that the system reliability and the maintenance cost are optimised simultaneously with all constraints obeyed. Notably, it is known from Model (27a, b) that not only objective functions but also constraints are well tailored for offshore wind farms. Two components of the cost criterion (the environmental monitoring cost $C_{i,t}^{EM}$ and the transportation cost $C_{i,t}^T$ in Eq. (9)), and six types of constraints (weather, manpower,

vehicle, greenhouse gas emission, marine ecosystem, and bird population constraints, see Eqs. (21)-(26)) are specially formulated for the PM of offshore wind farms.

Remark 1. Eliminating or adjusting some of the costs and constraints that have been implemented particularly for offshore wind farms, a generalized model of Model (27a, b) is applicable to general power systems.

On the other hand, the uniqueness of Model (27a, b) for offshore wind farms can be reflected from differences with the generalised model in wider scope. The convenience of transforming manifests the good applicability and flexibility of Model (27a, b), so that we can declare that the PM scheduling model proposed in this paper is reasonable. Furthermore, it is interesting that there exists another common method to represent the reliability maximization objective differently [8]. They define the corresponding objective function as the single objective in their generator maintenance scheduling problem of power systems like

$$\min_{\mathbf{X}} \sum_{t=1}^n \left[\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t \right]^2, \quad (28)$$

which is to quantify the reliability as the sum of squares of the net power reserve (SSR). Thus, the minimisation of the SSR implies the reliability maximization. This definition of the reliability objective is generated from another perspective that the high system reliability implies the little difference among the net power reserves for each time period, namely to make full use of the electric energy and avoid power waste. It is to pursue a high resource utilisation rate.

Therefore, we are going to employ this form of reliability maximisation objective function into our multi-objective, non-linear programming model for PM scheduling of offshore wind farms as well, in order to build a contrast (benchmark) model of Eqs. (27a, b) to compare with the one given by Eq. (28) after converting it into the range $[0, 1]$. To achieve this, we use the weight coefficient $1 / \sum_{t=1}^n (\sum_{i=1}^m p_{i,t} - d_t)^2$ of the SSR $[\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t]^2$. Thus, the equivalent form of this different maximisation objective function in Eq. (28) can be indicated as

$$\min_{\mathbf{X}} \sum_{t=1}^n \frac{[\sum_{i=1}^m p_{i,t}(1 - x_{i,t}) - d_t]^2}{\sum_{\tau=1}^n (\sum_{i=1}^m p_{i,\tau} - d_{\tau})^2}. \quad (29)$$

Thus, the contrast model of our problem is constructed by substituting the aforesaid reliability objective Eq. (7) in Eq. (27a) for the minimisation of the SSR Eq. (29), and remaining all the rest objective and constraints unchanged.⁶ In the later section, comparisons and analyses

⁶It should be pointed out that the two values of reliability from Eq. (27a) and from Eq. (29) are originated

between the maintenance scheduling optimisation model Eqs. (27a, b) and its contrast model for offshore wind farms will be made to have a careful investigation of their performances and characteristics.

5. Nondominated Sorting Genetic Algorithm II

The nondominated sorting genetic algorithm II (NSGA-II) utilised for solving the proposed Model (27a, b) for the PM scheduling of offshore wind farms is going to be introduced. Abundant Pareto-optimal solutions can be obtained from the NSGA-II. As none of Pareto-optimal solutions is absolutely better than any other one, each of them is acceptable [21]. Therefore, they can provide various trade-off solutions for determining a satisficing solution to support the decision-making of the offshore wind farm project.

The fast nondominated sorting procedure, the fast crowding distance estimation procedure, and the simple crowded-comparison operator are regarded as three innovations of the NSGA-II, so that weaknesses of NSGA are alleviated to a large extent owing to improvements in aspects of the computational complexity, elitism and diversity preservation. Thus, the whole procedure of the NSGA-II for solving the proposed Model (27a, b) is presented in Algorithm 1 in detail (see Appendix). It should be noted that the contrast model is also similarly solved by Algorithm 1.

Algorithm 1 NSGA-II for PM scheduling model of offshore wind farms

- 1: Set $t=1$;
 - 2: Initialize the parent population P_0 and set it as P_t with *pop_size* feasible solutions.
 - 3: Calculate values of objective functions Eqs. (7) and (11) in Model (27a) for all solutions in P_t .
 - 4: Rank solutions in P_t based on the fast nondominated sorting approach. So each solution i is assigned with a nondomination rank i_{rank} .
 - 5: Calculate the crowding distance $i_{distance}$ of each solution i in P_t based on the density estimation metric.
 - 6: Select *pop_size* solutions by the binary tournament selection utilizing the crowded comparison operator which is based on the nondomination rank i_{rank} and the crowding distance $i_{distance}$. The selected solutions are used to create an offspring population.
 - 7: Update solutions by crossover and mutation operations. The feasibility of offspring population Q_t should be checked by constraints Eqs. (12)-(26) in Model (27b).
 - 8: Execute the elitist strategy containing the combination and comparison of P_t and Q_t . $t \leftarrow t + 1$, and the new P_t with *pop_size* solutions is output for the next iteration.
 - 9: Repeat Steps 6-8 for a given number of iterations.
 - 10: Collect Pareto-optimal solutions to support the decision-making.
-

from two different reliability indices, which provide two different interpretations of the reliability ensured by power reserves.

6. Numerical Example

In order to verify the feasibility, effectiveness and performance of the proposed constrained non-linear multi-objective programming model for PM scheduling of offshore wind farms, Eqs. (27a, b), and its contrast model, as well as the corresponding NSGA-II, a hypothetical case of offshore wind farm preventive maintenance is illustrated as a numerical example. The results are analysed and compared from three main respects in this section.

6.1. Background and parameters

The case we are going to apply and implement is about an offshore wind farm with 50 wind turbines. The time horizon is 52 weeks of a year. Data of the generated energy $p_{i,t}$, the customer power demand d_t , all maintenance cost components $C_{i,t}^M$, $C_{i,t}^{EQ}$, $C_{i,t}^I$, $C_{i,t}^{EM}$, $C_{i,t}^T$, $C_{i,t}^A$ and $C_{i,t}^{CRM}$, the maintenance capacity LT_t , manpower demands M_i^V , M_i^H and M_i^L , the available manpower AM_t , vehicle demands V_i and H_i , available vehicle amounts AV_t and AH_t , all greenhouse gas emission related parameters z_i , q^V , q^H , \bar{w} , EQ_i^V , EQ_i^H and GHG , navigating vehicle limits LV_t and LH_t have already been estimated and set reasonably according to historical data and expertise (see Tables B.6–B.10 in Appendix). Besides, the maintenance duration LP_i of each turbine is 3 weeks. The maintenance of TR_5 is prior to that of TR_{16} . The deadline of TR_{27} is PR_{48} . The time set not allowed for maintenance is $U = \{1, 2, 3\}$. Parameter settings for NSGA-II are given in Table B.11 in Appendix.

6.2. Effects of different decision-maker's attitudes

As there are mainly four different kinds of decision-maker's attitudes towards the wind farm project over the time horizon, i.e., fully rational, optimism biased, wait-and-see and pessimism biased preferences, their different impacts on final solutions are shown in this section. It essentially means we need to assign attainment exponents s_1, s_2, \dots, s_{52} by various combinations of s_t with positive, neutral or negative effects in our case.

First, we allocate all 52 attainment exponents to four types of attitudes as shown in Table 3. As to the fully rational attitude (2nd and 8th columns), we select s_1, s_2, \dots, s_{18} randomly from $[0, 1)$, make $s_{19}, s_{20}, \dots, s_{34}$ all equal to 1, and choose $s_{35}, s_{36}, \dots, s_{52}$ randomly from $(1, 50)$, which can be approximately equivalent to the interval $(1, +\infty)$. For the optimism biased attitude (3rd and 9th columns), s_1, s_2, \dots, s_{52} are entirely from $[0, 1)$. For the wait-and-see attitude (4th and 10th columns), all s_t are equal to 1, which means no exponents exist and the same situation with that of the first conventional reliability criterion (the power reserve ratio). For the pessimism biased attitude, s_1, s_2, \dots, s_{52} in the 5th and 11th columns are randomly

Table 3: Assignment of attainment exponents s_t into different decision-maker's attitudes

s_t	Rat	Opt	W&s	Pes ¹	Pes ²	s_t	Rat	Opt	W&s	Pes ¹	Pes ²
s_1	0.21	0.58	1	47.50	2	s_{27}	1	0.03	1	2.06	2
s_2	0.29	0.12	1	19.21	2	s_{28}	1	0.24	1	17.95	2
s_3	0.70	0.41	1	9.78	2	s_{29}	1	0.97	1	23.91	2
s_4	0.71	0.67	1	15.47	2	s_{30}	1	0.15	1	2.22	2
s_5	0.72	0.68	1	4.85	2	s_{31}	1	0.84	1	7.84	2
s_6	0.23	0.01	1	3.44	2	s_{32}	1	0.48	1	39.87	2
s_7	0.84	0.81	1	10.17	2	s_{33}	1	0.07	1	8.92	2
s_8	0.93	0.70	1	32.29	2	s_{34}	1	0.40	1	5.05	2
s_9	0.41	0.17	1	35.85	2	s_{35}	14.04	0.66	1	40.52	2
s_{10}	0.69	0.61	1	27.68	2	s_{36}	40.11	0.78	1	27.84	2
s_{11}	0.25	0.29	1	38.26	2	s_{37}	23.70	0.33	1	22.65	2
s_{12}	0.79	0.37	1	4.26	2	s_{38}	19.45	0.74	1	28.53	2
s_{13}	0.96	0.72	1	6.63	2	s_{39}	49.97	0.44	1	43.74	2
s_{14}	0.53	0.27	1	11.81	2	s_{40}	39.96	0.02	1	22.35	2
s_{15}	0.95	0.11	1	24.01	2	s_{41}	3.63	0.23	1	27.27	2
s_{16}	0.01	0.06	1	18.02	2	s_{42}	45.28	0.86	1	40.59	2
s_{17}	0.12	0.06	1	18.60	2	s_{43}	46.61	0.79	1	5.31	2
s_{18}	0.40	0.04	1	47.53	2	s_{44}	23.06	0.07	1	7.99	2
s_{19}	1	0.06	1	16.15	2	s_{45}	36.72	0.48	1	4.51	2
s_{20}	1	0.16	1	20.32	2	s_{46}	28.96	0.91	1	40.40	2
s_{21}	1	0.78	1	14.56	2	s_{47}	36.90	0.82	1	9.90	2
s_{22}	1	0.19	1	40.26	2	s_{48}	15.47	0.60	1	35.70	2
s_{23}	1	0.17	1	1.45	2	s_{49}	9.09	0.48	1	4.38	2
s_{24}	1	0.44	1	29.57	2	s_{50}	6.96	0.07	1	35.08	2
s_{25}	1	0.97	1	10.37	2	s_{51}	42.39	0.87	1	30.01	2
s_{26}	1	0.69	1	47.58	2	s_{52}	21.46	0.56	1	46.84	2

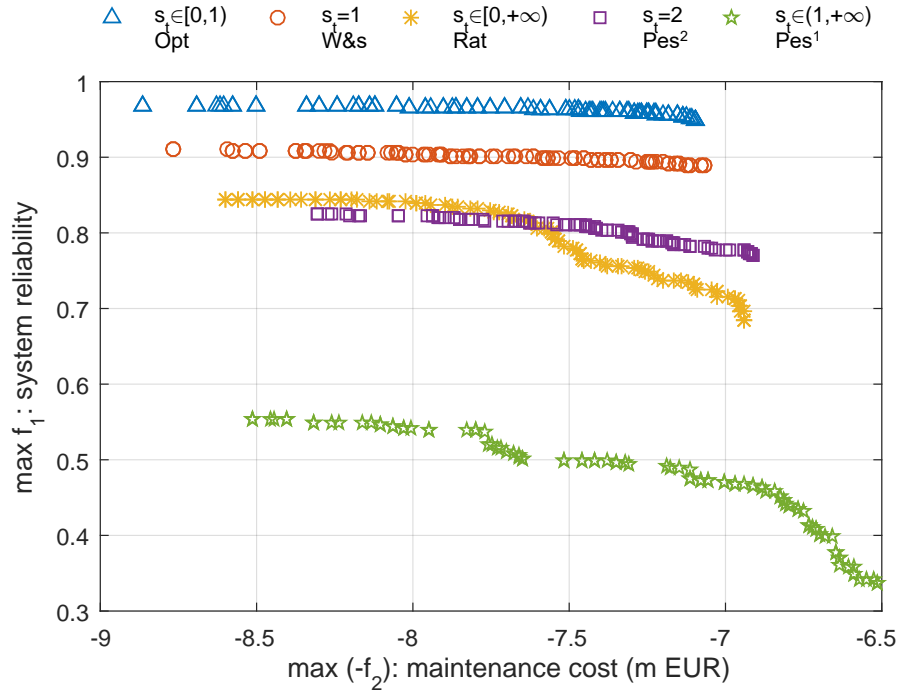


Fig. 2: Effects of different decision-maker's attitudes on solutions.

Table 4: Ranges of two objectives on different decision-maker's attitudes

Attitude	Reliability ^L	Reliability ^U	Cost ^L (m€)	Cost ^U (m€)
Rational	0.684	0.845	6.939	8.600
Optimistic	0.949	0.968	7.096	8.862
W&s	0.888	0.910	7.069	8.765
Pessimistic ¹	0.338	0.553	6.512	8.511
Pessimistic ²	0.770	0.824	6.914	8.305

picked from (1, 50), while those in the 6th and 12th columns are all set as $s_t = 2$, which is a special case for further comparison with the contrast model containing quadratic terms.

All five multi-objective programming models (based on Eqs. (27a, b)) are implemented for 5000 iterations, respectively and the final solutions are displayed in Fig. 2 by five different point types and also in Table 4. It is apparent from Fig. 2 and more precisely from Table 4 that results on the basis of the fully rational attitude (yellow asterisks in Fig. 2 and 2nd row in Table 4) have the best spread of Pareto-optimal solutions, which can provide much wider and more distinguishable choices both on system reliability (changes from 0.684 to 0.845) and maintenance cost (from €6.939m to €8.600m) directions for trading-off and supporting the decision-making. Although solutions with optimistic, wait-and-see and pessimistic ($s_t = 2$) attitudes achieve extremely high values of reliability, their solution sets contain a few gaps and their spreads are relatively narrow and partial on the reliability axis. Moreover, solutions with the pessimistic attitude ($s_t > 1$) form good spreads on both of the reliability and the cost axes, but their values of reliability are relatively too low (even the upper bound Reliability = 0.553). Hence, we can conclude that the fully rational attitude seems more appropriate for decision-makers to hold because it not only offers more diverse options, but also makes the results more reasonable and effective.

Thus, in the following analyses, we will primarily focus on the multi-objective optimization model with attainment exponents setting based on the fully rational attitude. Obviously, this is not an exhaustive and conclusive way, as different decision-makers can take an alternative strategy as the most preferable one. Actually, the model flexibility is one of the main advantage of our treatment.

6.3. Solutions and guidance for decision-making

In this section, we will analyse in detail the Pareto-optimal solutions of the proposed model (Eqs. (27a, b)), in order to provide a practical guidance for decision-making on the PM scheduling problem of offshore wind farms. Values of attainment exponents s_t are assigned according to the fully rational attitude, i.e., and the same with values in the 2nd and 8th columns of Table 3. In Fig. 3, asterisks represent Pareto-optimal solutions after 5000 iterations. We can extract some decision instructions aiming at different strategic environments of an offshore wind farm project as follows:

(1) If the offshore wind farm project executes a cost priority strategy, it means that decision-makers put the maintenance cost as the first consideration and want to save as much as possible. To pursue low cost implies to sacrifice the achievement of the system reliability. As long as

the reliability is not so low that it will influence the basic stability, decision-makers are willing to adopt a solution with the cost close to the lowest and the low but acceptable reliability. For example, the solution with the lowest cost as €6.939m and reliability as 0.684 among all results, i.e., the asterisk on the bottom right corner in Fig. 3, can be chosen as a decision of

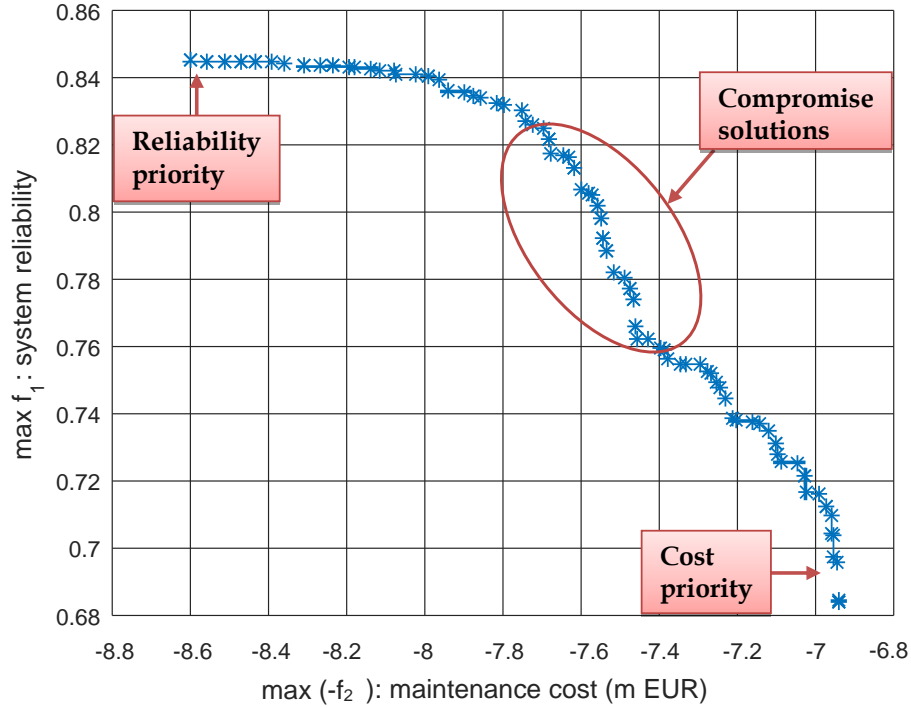
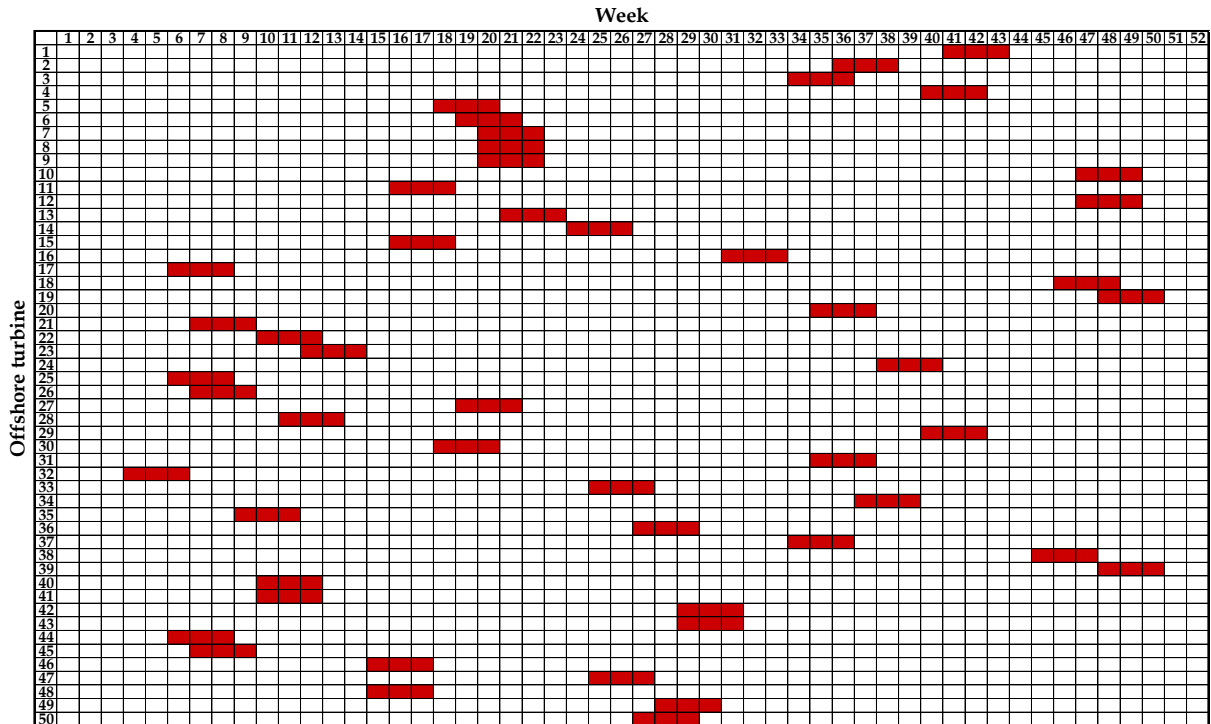


Fig. 3: Pareto-optimal solutions after 5000 iterations with the fully rational attitude.



(a) PM schedule of a cost priority solution.

Fig. 4: Example Schedules of different Pareto-optimal solutions.

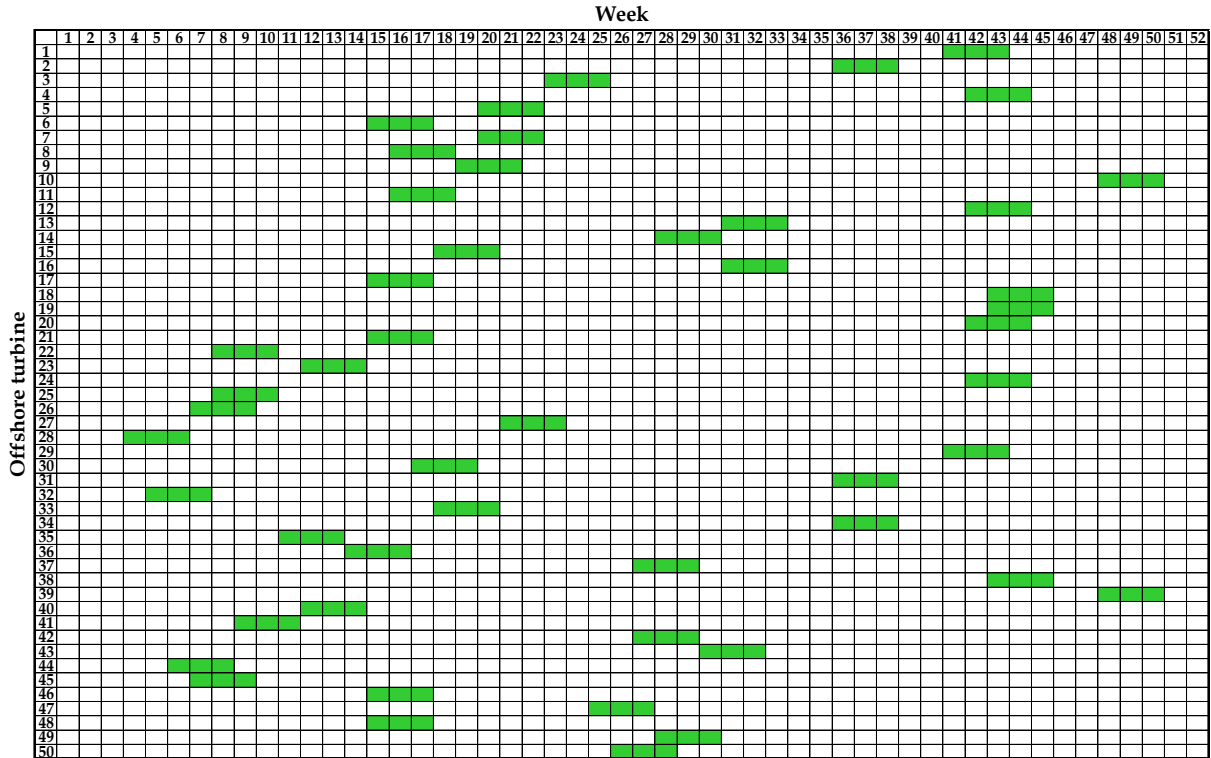
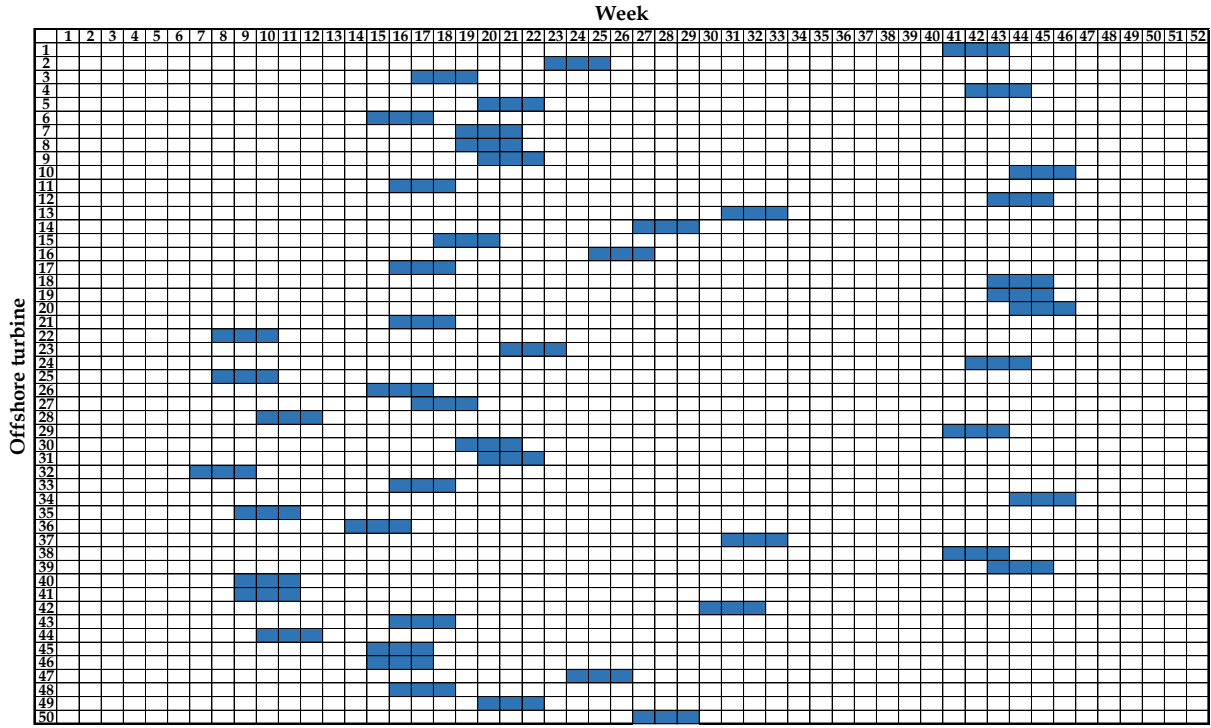


Fig. 4: Example Schedules of different Pareto-optimal solutions.

Table 5: Examples of Pareto-optimal solutions for different strategic environments

(a) Pareto-optimal solutions for cost priority strategy					
Solution	Reliability	Cost (m€)	Solution	Reliability	Cost (m€)
1	0.684	6.939	4	0.713	6.972
2	0.696	6.943	5	0.722	7.027
3	0.704	6.954	6	0.731	7.101
(b) Pareto-optimal solutions for reliability priority strategy					
Solution	Reliability	Cost (m€)	Solution	Reliability	Cost (m€)
1	0.845	8.600	4	0.841	8.025
2	0.844	8.359	5	0.840	7.991
3	0.843	8.194	6	0.836	7.942
(c) Pareto-optimal solutions for compromise strategy					
Solution	Reliability	Cost (m€)	Solution	Reliability	Cost (m€)
1	0.762	7.428	4	0.798	7.549
2	0.774	7.466	5	0.806	7.601
3	0.788	7.536	6	0.818	7.676

cost priority. The corresponding maintenance schedule of this solution is shown in Fig. 4a, in which the blocks refer to periods in maintenance. In addition, five other cost priority solutions are given in Table 5a.

(2) If the offshore wind farm project carries out a reliability priority strategy, which implies that the customer demand satisfaction is more significant to decision-makers and they have sufficient investments so that the maintenance budget is not a significant problem, Pareto-optimal solutions in the top left corner of Fig. 3 are their best choices. As long as the maintenance cost does not exceed the budget, higher reliability level can be aspired. The upper bound decision with the highest reliability can be easily found in the figure. It reaches the reliability as 0.845 and the cost as €8.600m as a compensation. The corresponding maintenance schedule of this solution is shown in Fig. 4b. Also, five other reliability priority solutions are listed in Table 5b. It is notable that the blocks are concentrated in relatively early periods and there are no more turbines in maintenance from PR_{34} to PR_{40} and since PR_{47} . The reason for this phenomenon is that when decision-makers hold the fully rational attitude, settings of attainment exponents s_t with this attitude have already decided that the high reliability signifies maintaining as early as possible. Differences in distributions of schedules tend to be the most obvious between two solutions with the lower bound of cost and the upper bound of reliability which can be observed from Fig. 4a and Fig. 4b.

(3) If both the maintenance cost and the system reliability are important and almost unbiased to the project strategy in eyes of decision-makers, some compromise solutions should be considered. Compromise solutions mean those not sacrificing a lot on the optimization of either objective function, so which also implies a particularly outstanding optimised direction can

also not be reached among these solutions. They are marked in the circle in Fig. 3, and six compromise solutions are listed in Table 5c. The maintenance schedule of the first solution in Table 5c is indicated in Fig. 4c. It can be seen that the distribution of the schedule in Fig. 4c has less obvious centralised tendency than those in Fig. 4a and Fig. 4b.

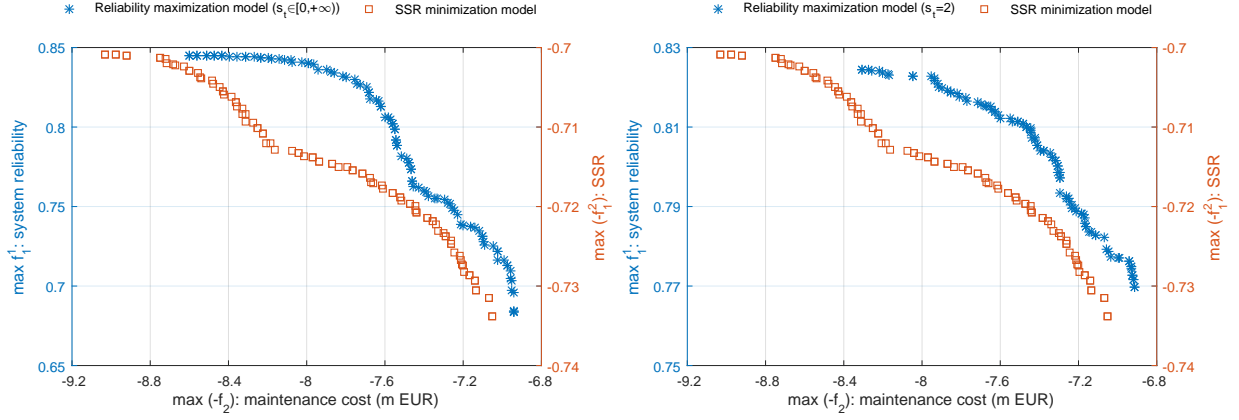
To sum up, it can be seen that no matter what strategy the offshore wind farm project adopts, Pareto-optimal solutions obtained from the optimisation are able to provide adequate alternative satisfying solutions to decision-makers. According to Porter's generic strategies [38], when decision-makers take adopt a cost leadership strategy for offshore wind farm maintenance especially in the early time of the project, a decision can be selected from solutions in the bottom right corner of Fig. 3. When the execution of the project begins to stabilise, the differentiation strategy (i.e., the customer-oriented strategy) is more likely to be adopted in order to satisfy customer needs for more profits. On this occasion, the primary mission is to pursue high reliability, which means to make a decision from the solutions in the top left corner of Fig. 3. When the focus strategy is taken to consider the cost and the customer satisfaction simultaneously, decision-makers are not partial to either of the two objectives. A decision to support this coordination strategy can be made from solutions in the circle of Fig. 3. [The maintenance schedule solutions corresponding to a certain maintenance strategy \(cost leadership, differentiation, or focus strategies\) can be timely and newly obtained by implementing the model and algorithm again after constraining those wind turbines that already completed the maintenance jobs in the past periods, whenever the decision-maker determines to switch to a different strategy from the present one at any period during the time horizon.](#)

6.4. Comparisons between the two reliability objectives

In this section, we make comparisons between two approaches (i.e., the reliability maximisation and the SSR minimisation) of the system reliability maximisation objective in the proposed model, Eqs. (27a, b), and its contrast model. Comparisons are made twice, one is the proposed model with the fully rational attitude vs. the contrast model, and the other is the proposed model with attainment exponents $s_t = 2$ vs. the contrast model because it contains quadratic terms.

Results of the two comparisons are shown in the following Fig. 5a and Fig. 5b, which are found to be almost similar. It should also be noted that in both figures, the left vertical axis is for Model (27a, b) and the right vertical axis is for its contrast model. Hence, some synthetical conclusions can be drawn from the two figures:

- (1) The maintenance cost of Model (27a, b) can achieve lower results than that of the contrast



(a) Proposed model with fully rational attitude vs. its contrast model. (b) Proposed model with $s_t = 2$ vs. the contrast model.

Fig. 5: Comparisons between two reliability objectives.

model, and some high values of the cost that the contrast model includes are not in the value range of Model (27a, b). Consequently, Model (27a, b) has an obvious cost advantage over its contrast model.

(2) With respect to the system reliability, it can be seen from Fig. 5a that the range of the reliability distribution of Model (27a, b) (approximately 0.16) is much wider than that of the contrast model (approximately 0.03), which means Model (27a, b) can offer a better decision support and more reliability choices than its contrast model.

7. Conclusions

In this paper, we contribute to the corresponding literature in the following four ways: (i) we optimise the reliability and cost objectives simultaneously in the PM scheduling problem with the background of offshore wind farms, making the problem more comprehensive and closer to reality; (ii) we propose a new definition of the reliability criterion by utilising an attainment exponent which can be regarded as an expansion of previous definitions; (iii) we also well design the components of the maintenance cost criterion and constraints particularly applicable to the offshore wind farm environment; (iv) we employ the NSGA-II to solve our constrained non-linear multi-objective programming model for the PM scheduling of offshore wind farms, and obtain a set of Pareto-optimal solutions for supporting decision-making.

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Appendix A. Nondominated Sorting Genetic Algorithm II [13]

Appendix A.1. Fast nondominated sorting procedure

For each individual p in the population of size N , two entities are calculated: (1) S_p , a set of individuals that the individual p dominates, and (2) domination count n_p , the number of individuals which dominate the individual p .

All individuals in the first nondominated front will have their domination count as zero. Now, for each individual p in the first front, we visit each member q of its set S_p and reduce its domination count by one. In doing so, if for any member q , the domination count becomes zero, we put it in a separate list Q . These members belong to the second nondominated front. Next, the above procedure is continued with each member of Q and the third front is identified. This process continues until all fronts are identified. Thus, the pseudocode of fast nondominated sorting approach which requires $O(mN^2)$ computations are shown in Algorithm 2.

Algorithm 2 Fast-non-dominated-sort (P)

```

1: for each  $p \in P$  do
2:    $S_p = \emptyset$ 
3:    $n_p = 0$ 
4:   for each  $q \in P$  do
5:     if  $p \prec q$  then ▷ If  $p$  dominates  $q$ 
6:        $S_p = S_p \cup \{q\}$  ▷ Add  $q$  to the set of solutions dominated by  $p$ 
7:     else if  $q \prec p$  then
8:        $n_p = n_p + 1$  ▷ Increment the domination counter of  $p$ 
9:     end if
10:  end for
11:  if  $n_p = 0$  then ▷  $p$  belongs to the first front
12:     $p_{rank} = 1$ 
13:     $\mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}$ 
14:  end if
15: end for
16:  $i = 1$  ▷ Initialize the front counter
17: while  $\mathcal{F}_i \neq \emptyset$  do
18:    $Q = \emptyset$  ▷ Used to store the members of the next front
19:   for each  $p \in \mathcal{F}_i$  do
20:     for each  $q \in S_p$  do
21:        $n_q = n_q - 1$ 
22:       if  $n_q = 0$  then ▷  $q$  belongs to the next front
23:          $q_{rank} = i + 1$ 
24:          $Q = Q \cup \{q\}$ 
25:       end if
26:     end for
27:   end for
28:    $i = i + 1$ 
29:    $\mathcal{F}_i = Q$ 
30: end while

```

Appendix A.2. Fast crowding distance estimation procedure

In the proposed NSGA-II, the sharing function approach that the original NSGA used is replaced with a crowded-comparison approach which no longer requires any user-defined parameter for maintaining sustainable diversity among population members and has a better computational complexity.

To describe this approach, a density-estimation metric is firstly defined to get an estimate of the density of individuals surrounding a particular individual in the population. We calculate the average distance of two points on either side of this point along each of the objectives. This quantity $i_{distance}$ serves as an estimate of the perimeter of the cuboid formed by using the nearest neighbours as the vertices (called the crowding distance). The Algorithm 3 outlines the crowding distance computation procedure of all individuals in a nondominated set I and has $O(mN \log N)$ computational complexity.

Algorithm 3 Crowding-distance-assignment (\mathcal{I})

```

1:  $l = |\mathcal{I}|$  ▷ number of solutions in  $\mathcal{I}$ 
2: for each  $i$  do ▷ initialize distance
3:   set  $\mathcal{I}[i]_{distance} = 0$ 
4: end for
5: for each objective  $m$  do
6:    $\mathcal{I} = \text{sort}(\mathcal{I}, m)$  ▷ sort using each objective value
7:    $\mathcal{I}[1]_{distance} = \mathcal{I}[l]_{distance} = \infty$  ▷ so that boundary points are always selected
8:   for  $i = 2$  to  $(l - 1)$  do ▷ for all other points
9:      $\mathcal{I}[i]_{distance} = \mathcal{I}[i]_{distance} + (\mathcal{I}[i + 1].m - \mathcal{I}[i - 1].m) / (f_m^{max} - f_m^{min})$ 
10:  end for
11: end for

```

Appendix A.3. Simple crowded-comparison operator

The crowded-comparison operator (\prec_n) guides the selection and elitism procedure at various stages of the algorithm to a uniformly spread-out Pareto-optimal front. In the selection step of this algorithm, we use a binary tournament selection based on crowded-comparison operator. Furthermore, in the elitist strategy, we utilise crowded-comparison operator to reduce the population. Each individual i in the population has two attributes: (1) nondomination rank i_{rank} , and (2) crowding distance $i_{distance}$. A partial order \prec_n is defined as follows,

$$\begin{aligned}
 i \prec_n j \quad & \text{if } (i_{rank} < j_{rank}) \\
 & \text{or } ((i_{rank} = j_{rank}) \text{ and } (i_{distance} > j_{distance})).
 \end{aligned} \tag{A.1}$$

The individual with a lower rank is preferred between two individuals with different non-domination ranks or, if both individuals belong to the same front, we prefer the individual that

is located in a less crowded region. The complexity of sorting on crowded-comparison operator is $O(N \log N)$.

Appendix A.4. Crossover and mutation operator

As this algorithm is based on real coding, it uses simulated binary crossover (SBX) operator for crossover process and polynomial mutation for mutation process. Distribution indexes η_c and η_m are used for crossover and mutation operators [13].

Appendix A.5. Elitist strategy

Elitism is to ensure that the excellent individuals in parent population can be selected to form the new parent population. It can speed up the performance of the GA significantly, which can also help in preventing the loss of good individuals once they are found. It needs to compare current population with the previously found best nondominated individuals, so we first describe the t th generation of the proposed Algorithm 4.

Algorithm 4 Elitist-strategy (P_t)

1: $R_t = P_t \cup Q_t$	▷ combine parent and offspring population
2: $\mathcal{F} = \text{Fast-non-dominated-sort}(R_t)$	▷ $\mathcal{F} = (\mathcal{F}_1, \mathcal{F}_2, \dots)$, all nondominated fronts of R_t
3: $P_{t+1} = \emptyset$ and $i = 1$	
4: while $ P_{t+1} + \mathcal{F}_i \leq N$ do	▷ until the parent population is filled
5: Crowding-distance-assignment(\mathcal{F}_i)	▷ calculate crowding-distance in \mathcal{F}_i
6: $P_{t+1} = P_{t+1} \cup \mathcal{F}_i$	▷ include i th nondominated front in the parent pop
7: $i = i + 1$	▷ check the next front for inclusion
8: end while	
9: sort(\mathcal{F}_i, \prec_n)	▷ sort in descending order using \prec_n
10: $P_{t+1} = P_{t+1} \cup \mathcal{F}_i[1 : (N - P_{t+1})]$	▷ choose the first $(N - P_{t+1})$ elements of \mathcal{F}_i
11: $Q_{t+1} = \text{Make-new-pop}(P_{t+1})$	▷ use selection, crossover and mutation to create a new population Q_{t+1}
12: $t = t + 1$	▷ increment the generation counter

The new parent population P_{t+1} of size N is now used in the next generation or cycle for selection, crossover and mutation to create a new offspring population of size N .

Until now, the whole cycle of NSGA-II has been introduced. The overall computational complexity of the algorithm is $O(mN^2)$, which is up to the nondominated sorting procedure of the algorithm. The fast nondominated sorting procedure, the fast crowding distance estimation procedure, and the simple crowded-comparison operator are regarded as three innovations of NSGA-II, where the weaknesses of NSGA have been alleviated to a large extent owing to the improvements they brought in aspects of computational complexity, elitism and diversity preservation. Based on the previous literature, we conclude a complete process of this algorithm given in Fig. A.6.

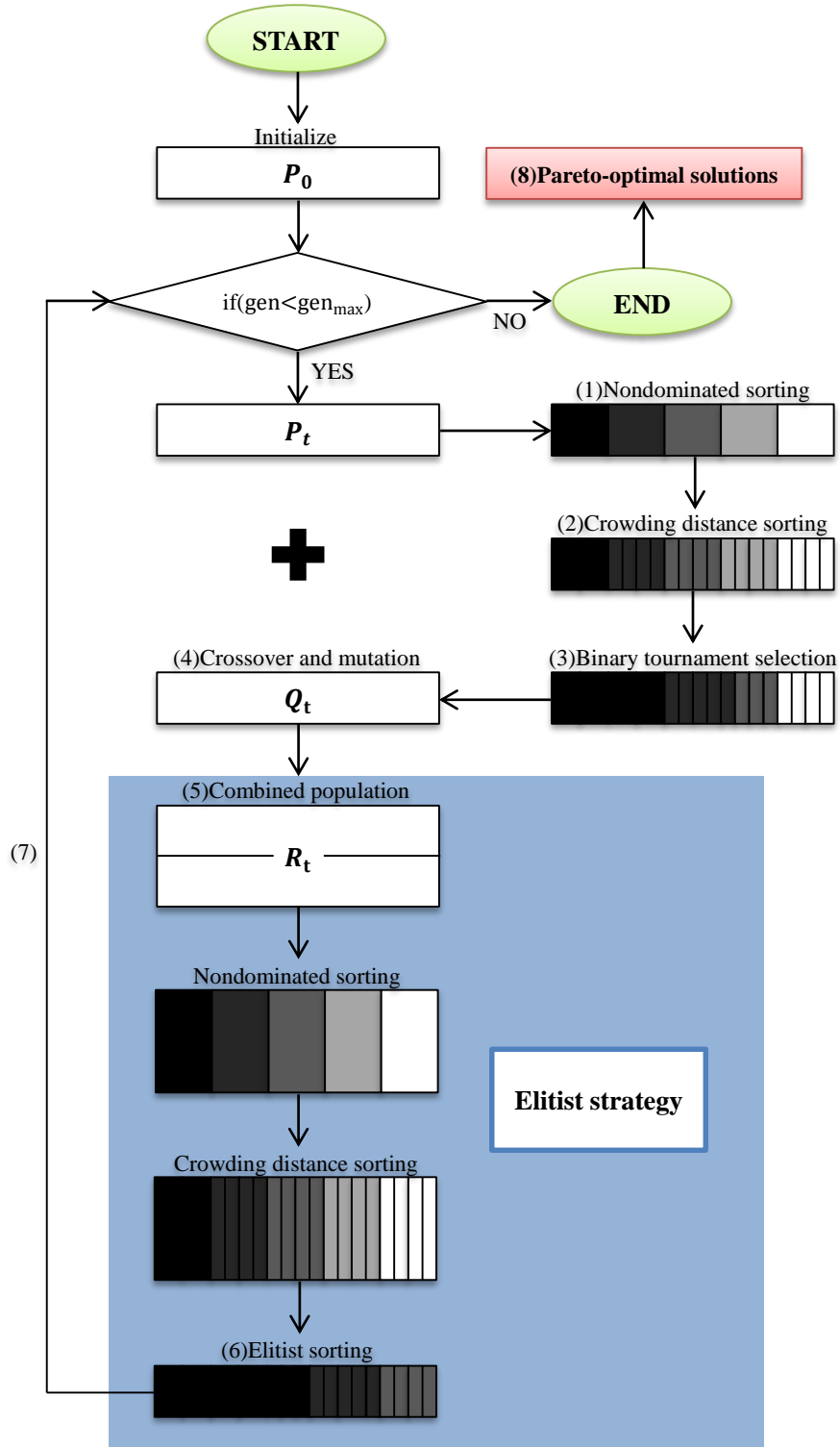


Fig. A.6: Process of NSGA-II.

Appendix B. Parameter settings of the model for the numerical example

Table B.6: Power generated $p_{i,t}$ and demanded d_t (10 kW)

Table B.7: Total maintenance cost $C_{i,t}$ (10^2 EUR)[illegible]

Table B.8: Parameters vary on different turbines

	TH_1	TH_2	TH_3	TH_4	TH_5	TH_6	TH_7	TH_8	TH_9	TH_{10}	TH_{11}	TH_{12}	TH_{13}	TH_{14}	TH_{15}	TH_{16}	TH_{17}	TH_{18}	TH_{19}	TH_{20}	TH_{21}	TH_{22}	TH_{23}	TH_{24}	TH_{25}	TH_{26}	TH_{27}	TH_{28}	TH_{29}	TH_{30}	TH_{31}	TH_{32}	TH_{33}	TH_{34}	TH_{35}	TH_{36}	TH_{37}	TH_{38}	TH_{39}	TH_{40}	TH_{41}	TH_{42}	TH_{43}	TH_{44}	TH_{45}	TH_{46}	TH_{47}	TH_{48}	TH_{49}	TH_{50}	
M^V	6	4	3	6	6	4	5	4	3	4	3	3	4	3	2	3	4	3	2	3	4	2	3	6	4	2	3	4	2	3	4	2	3	4	2	3	3	4	2	3	3	4	2	3	4	2	3	4	6	4	
M^H	0	3	0	0	1	0	0	2	3	2	0	2	3	1	0	3	2	3	1	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
M^L	3	2	2	3	1	1	1	3	4	1	4	1	2	5	3	1	3	1	3	2	3	3	3	2	3	1	3	1	3	1	4	3	2	4	1	1	2	2	1	1	2	2	1	1	3	2	1	3	2	1	3
V	3	2	2	3	3	2	3	2	2	2	2	2	2	3	1	2	2	2	2	3	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	3	2
H	0	2	0	0	1	0	0	1	2	1	0	1	1	2	1	0	2	1	2	0	1	0	1	2	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
ϵ (km)	35	39	86	62	48	61	54	62	54	68	52	99	27	38	18	15	42	46	36	71	69	72	65	84	25	21	66	37	52	52	79	49	41	64	70	52	38	22	57	31	13	71	29	45	65	39	69	41	65	67	
$\rho_{QV}^{\text{1000}}(\text{kg})$	1405	2866	1778	2321	1414	2505	1607	2305	2723	2671	2126	1209	1072	3264	1281	2065	2346	3461	1395	2107	1266	3465	1011	2038	3044	3172	1211	1999	1649	3000	2678	1454	1659	1505	1340	3174	2449	2275	1262	1262	2004	2283	2004	1189	1600	1308	1459	1600			
$\rho_{QM}^{\text{1000}}(\text{kg})$	980	741	1131	880	716	1246	1189	895	960	928	587	671	824	667	1100	575	603	553	605	792	680	1231	787	561	1215	1262	795	500	687	782	687	686	1121	426	1236	1056	840	921	613	813											

Table B.9: Parameters vary on different time periods

	PT ₀	PT ₂	PT ₃	PT ₄	PT ₅	PT ₆	PT ₇	PT ₈	PT ₉	PT ₁₀	PT ₁₁	PT ₁₂	PT ₁₃	PT ₁₄	PT ₁₅	PT ₁₆	PT ₁₇	PT ₁₈	PT ₁₉	PT ₂₀	PT ₂₁	PT ₂₂	PT ₂₃	PT ₂₄	PT ₂₅	PT ₂₆	PT ₂₇	PT ₂₈	PT ₂₉	PT ₃₀	PT ₃₁	PT ₃₂	PT ₃₃	PT ₃₄	PT ₃₅	PT ₃₆	PT ₃₇	PT ₃₈	PT ₃₉	PT ₄₀	PT ₄₁	PT ₄₂	PT ₄₃	PT ₄₄	PT ₄₅	PT ₄₆	PT ₄₇	PT ₄₈	PT ₄₉	PT ₅₀	PT ₅₁						
LZ	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6					
AM	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	62	
AV	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	
AM	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	
LV	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	
LB	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

Table B.10: Remaining parameters

Model parameter	Parameter value
q^V (kg/kg·km)	10^{-5}
q^H (kg/kg·km)	2×10^{-4}
w (kg)	65
GHG (kg)	110

Table B.11: Parameters for NSGA-II

NSGA-II parameter	Parameter value (type)
Population size, N	100
Length of individual, M	50
Number of maximum generations, $maxgen$	5000
Crossover probability, p_c	0.54
Mutation probability, p_m	0.06
Crossover index, η_c	20 (simulated binary crossover)
Mutation index, η_m	20 (polynomial mutation)